Ecological Indicators 89 (2018) 771–780

Contents lists available at ScienceDirect

Ecological Indicators

journal homepage: www.elsevier.com/locate/ecolind

Original Articles

Extent of vulnerability in wheat producing agro-ecologies of India: Tracking from indicators of cross-section and multi-dimension data

R. Sendhil[a,*], Ankita Jha[b], Anuj Kumar[c], Satyavir Singh[c]

[a] Scientist (Agricultural Economics), Social Sciences, ICAR-Indian Institute of Wheat and Barley Research, Karnal 132 001, Haryana, India
[b] Scientist (Agricultural Meteorology), Resource Management, ICAR-Indian Institute of Wheat and Barley Research, Karnal 132 001, Haryana, India
[c] Principal Scientist (Agricultural Extension), Social Sciences, ICAR-Indian Institute of Wheat and Barley Research, Karnal 132 001, Haryana, India

ARTICLE INFO

Keywords:
Wheat
Climate vulnerability
Principal component analysis
Climate smart farming

ABSTRACT

India's geography, monsoon dependency and weather anomalies place wheat production prospects and sustainability at crossroads across agro-ecologies owing to its vulnerability. An attempt has been made to track the vulnerability in wheat producing regions for climate smart farming in India sourcing relevant historical data on multi-dimensional indicators for sensitivity, exposure and adaptive capacity. The composite vulnerability index has been estimated for 16 wheat growing states using the Intergovernmental Panel on Climate Change (IPCC) approach. First, the variables were normalised to make them unit free for comparison and second, weights were assigned to each variable across three dimensions (sensitivity, exposure and adaptive capacity) using the principal component analysis. Later, the regions were categorised into three groups based on the magnitude of the index *viz.*, high, moderate, and less. Jharkhand registered the highest sensitivity (0.61) while Punjab registered the lowest (0.18). Considering the exposure of regions to various climatic and weather variables in the wheat growing season (*Rabi*: November-April), it was found that Jharkhand had the highest exposure (0.48) and Punjab witnessed the lowest (0.30). In terms of adaptation to climate change, it was found that Maharashtra (0.63) had the highest adaptive capacity, followed by Haryana and Punjab. On the contrary, Jharkhand had the lowest adaptive capacity (0.21). Overall, the analysis of cross-sectional and multi-dimensional data indicated that Jharkhand is the most vulnerable region and Punjab is the least vulnerable region across wheat producing ecologies. Vulnerability mapping indicated that the magnitude of vulnerability is high in five regions (contributing 19% of total production), moderate in six regions (12% production) and low in five wheat growing regions (69% production). Regional prioritization has to be made *in lieu* of deviation in area and yield to minimize production losses. Further, adaptive measures and climate smart farming need to be practiced at farm and regional levels by formulating suitable policies and investment plans.

1. Introduction

Global warming is one of the alarming issues of the 21st century and the mean temperature is expected to increase more in the near future. Anthropogenic green house gas (GHG) emissions have increased since pre-industrial era and have led to unparalleled atmospheric concentrations of carbon dioxide, methane and nitrous oxide (Climate Change, 2014). Burning of fossil fuels and land use changes has boosted the quantities of GHGs and has the potential to alter the present climate system. The Intergovernmental Panel on Climate Change (IPCC) which was established during 1988 in response to the widespread human induced GHG emissions reported that among others, agriculture sector is going to be affected in a larger scale due to its vulnerable nature to climate change. The adverse effects are going to be more in the developing countries (Kato et al., 2011). However, the impact on productivity will be different among crops and regions. The yield levels are projected to increase and extend northwards, especially for cereals and winter crops in mid and high latitudes (Maracchi et al., 2005; Tuck et al., 2006; Olesen et al., 2007). Crops prevalent in plains of southern Europe *viz.* maize, sunflower and soybean could also become feasible at higher altitudes (Hildén et al., 2005; Audsley et al., 2006; Olesen et al., 2007). In this scenario, crop yield could increase by as much as 30% by 2050s, (Alexandrov et al., 2002; Ewert et al., 2005; Richter and Semenov, 2005; Audsley et al., 2006; Olesen et al., 2007).

In wheat, the cereal with maximum acreage in the world, climate change strongly influences the yield (Rao and Sinha, 1994; Ortiz et al., 2008) because of its sensitivity (Sendhil et al., 2016). The future climate scenarios evince that global warming may be beneficial in some

* Corresponding author.
E-mail address: r.sendhil@icar.gov.in (R. Sendhil).

https://doi.org/10.1016/j.ecolind.2018.02.053
Received 1 January 2018; Received in revised form 17 February 2018; Accepted 22 February 2018
1470-160X/ © 2018 Elsevier Ltd. All rights reserved.

regions, but could trim down the productivity in agro-ecologies where optimal temperature already exists. In certain regions like arid and tropics, wherein the likelihood of temperature matching with the physiological maxima for crops, further rise in temperature is expected to be detrimental as it would increase the heat stress and rate of evaporation. Alternatively, it has been predicted that an increase in the micro environment temperature by 2 °C in the mid-latitudes may increase the wheat output to the tune of 10% but in low-latitudes the yield levels could fall by the same amount (Gornall et al., 2010). The Indo-Gangetic Plains (IGPs) which accounts for 15% of global wheat production and comprises a part of the favorable, high potential, irrigated, low rainfall mega-environment might be reclassified as a heat-stressed, irrigated, short-season production mega-environment as a result of possible climate shifts by 2050 and this shift would also correspond to a significant reduction in wheat yields, unless appropriate cultivars and crop management practices are offered to and also are adopted by South Asian farmers (Ortiz et al., 2008).

Yield sensitivity to weather anomalies is a major concern in view of climate smart farming and is expected to have a negative effect on crop production especially in the vulnerable areas, thereby, affecting the country's food security (Sendhil et al., 2015; Sendhil et al., 2016; Sendhil et al., 2017b). India is highly vulnerable to climate change (World Bank, 2003; Rao et al., 2011; ECSJ, 2017) owing to its undulating topography which is clearly distinguished by the mighty Himalayan glaciated peaks and a long coastline; and a climate that ranges between temperate to tropical. As far as the impacts of global warming are concerned, the country is among the highly vulnerable groups and by far, agriculture sector is being affected largely. Indian agriculture, a livelihood source for about 58% of the population, forms the mainstay of its economy and is heavily dependent on vagaries of monsoons. Indian scientists from time to time have reported increasingly erratic monsoon rains, with more frequent and intense extreme events such as drought, cyclones and floods. Extreme rainfall events are likely to increase and altered trends across India have been noticed with respect to minimum temperatures (ECSJ, 2017). India is already experiencing these climate shifts which are being witnessed in the past few years and the variability of climate over the Indian sub-continent will continue to increase.

Vulnerability refers to the degree by which a region becomes susceptible to climate change. Literature on vulnerability assessment in different sectors and farm households are common, but to our knowledge, assessment of vulnerability using multi-dimension indicators to a particular crop in general and precisely cold loving plant like wheat which is highly sensitive to the climate change has not been done hitherto. In the milieu, to adapt and/or mitigate the climate change effects on wheat, an attempt has been made to track the degree of vulnerability and address the expected consequence that climate change may likely to inflict on wheat production from India. Further, the study is expected to help the policy makers to integrate vulnerable regions with relevant adaptation strategies and promote climate smart farming practices in all vulnerable regions to counter the ill-effects of climate change.

2. Material and methods

2.1. Study area

In India, wheat has been cultivated in 30.6 million hectares which falls in about 427 districts of 29 states (DES, 2017). In some states, particularly in South India like Tamil Nadu, Kerala, Andhra Pradesh and Karnataka only in a few pockets wheat is being cultivated. Barring a few states like Uttar Pradesh, Madhya Pradesh, Punjab, Rajasthan, Haryana and Bihar that accounts for about 87% of the crop area and 91% of production, the rest have marginal share (Ramdas et al., 2012). The present study has purposively chosen 16 wheat growing states to track the vulnerability status considering the data availability on different parameters and these states altogether contribute 99.39% share in total production.

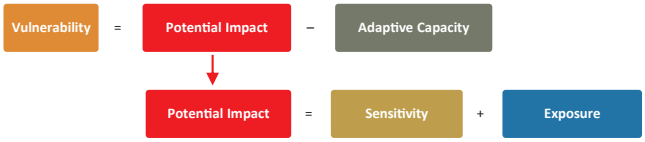


Fig. 1. Vulnerability and its determinants.

2.2. Vulnerability and its estimation

Vulnerability is the degree to which a region is susceptible to climatic risks and variability owing to the change in the climate over a period of time and is accounted by three indicators *viz.,* sensitivity, exposure and adaptive capacity (IPCC, 2007). Sensitivity is the degree to which a region responds to climate stimuli. Exposure is the degree to which a region is exposed to frequent risks and weather anomalies due to climate change. Sensitivity and exposure in combination termed as 'potential impact' which is highly detrimental to the region if the degree of the index is more. Alternatively, adaptive capacity is the ability of a region or production system to better adjust to the climatic risks, variability and impact due to climate change (Smit et al., 1999; Kumar et al., 2016). Ultimately, vulnerability index of a region is the degree of potential impact over adaptive capacity of that region (Fig. 1).

2.2.1. Data and sources

Secondary data on relevant variables have been coherently selected under sensitivity, exposure and adaptive capacity keeping in view of our study objectives, data availability, past studies (Gbetibouo and Ringler, 2009; Antwi-Agyei et al., 2012; Piya et al., 2012; Liu et al., 2013; Acheampong et al., 2014; Geng et al., 2014; Kumar et al., 2016) and experts opinion. The data were sourced from the Ministry of Agriculture and Farmers Welfare, Indian Meteorological Division, Indiastat portal, Ministry of Water Resources and other official publications and reports from the Government of India.

2.2.1.1. Variables on sensitivity and functional relationship. Sensitivity includes the response of the region to both problematic (positive functional relationship with sensitivity) as well beneficial stimuli (negative functional relationship with sensitivity) against climate change (Smit et al., 1999; IPCC, 2007). Under sensitivity both short-term and long-term changes which lead to vulnerability in wheat agro-ecologies have been taken into account and presented in Table 1 along with the expected functional relationship with sensitivity. Accordingly wheat area, production, and yield for the triennium ending (TE: Three years average) 2015–16 indicating the short-term spatial variation across 16 states having negative association with sensitivity; % change in area, production and yield for the TE 2006–07 to TE 2015–16; and, coefficient of variation in area, production and yield between TE 2006–07 and TE 2015–16 indicating the long-term inequality in wheat agro-ecologies exhibiting positive association with sensitivity were captured since there exists a significant regional disparity (Sharma et al., 2015). The potential loss due to climate variability from TE 2006–07 to TE 2015–16 was considered under sensitivity since it indicates the production loss across regions arising out of area deviation and yield deviation as well as their interaction effect using the formula developed by Kumar et al. (2016).

$$\text{Potential loss in wheat}_{\text{State}} = \frac{1}{t_n}\left[\sum_{t=1}^{n} Y_t(A_m - A_t) + \sum_{t=1}^{n} A_t(Y_m - Y_t) + \sum_{t=1}^{n} (A_m - A_t)(Y_m - Y_t)\right]$$

Table 1
Variables on sensitivity and their functional relationship.

Indicator	Variables	Functional relationship
Sensitivity	Area, production and yield (TE 2015–16) respectively in '000 ha, '000 tonnes and kg/ha	Negative
	% Change in area, production and yield (TE 2006–07 to TE 2015–16)	Positive
	CV for area, production and yield (TE 2006–07 to TE 2015–16) in %	Positive
	Potential loss (TE 2006–07 to TE 2015–16) in '000 tonnes	Positive
	Share of wheat in gross cropped area (TE 2015–16)	Negative
	Groundwater level (2011) in metres below ground	Positive
	% Holdings of small and marginal farmers (2011 Census)	Positive
	% area of small and marginal farmers (2011 Census)	Positive
	Farmer suicide (QE 2015–16) in number	Positive

Note: TE refers to triennium ending and QE refers to quinquennial ending.

where,

Y_t is the actual wheat yield for t^{th} year
A_t is the actual wheat area for t^{th} year
Y_m is the potential wheat yield achieved between TE 2006–07 and TE 2015–16
A_m is the potential wheat area recorded between TE 2006–07 and TE 2015–16

The share of wheat in gross cropped area (TE 2015–16) for 16 states exhibits negative functional relationship indicating less sensitivity if the state has more percentage of area under the crop. Declining groundwater level is an indicator variable showing the problematic stimuli of climate change resulting in higher risk for crop production (Cao et al., 2015). Hence the variable was considered under sensitivity. The percentage holdings of small and marginal farmers, and their area share with respect to wheat as per the latest 2011 agricultural census were accounted since farming by these small and marginal land holders under resource poor conditions is largely dependent on climatic risks and variability (Conway, 2009; Gbetibouo and Ringler, 2009). Unlike other studies barring estimation of household vulnerability (Piya et al., 2012), the number of farmer suicide for the quinquennial ending 2015–16 was considered for indexing regional vulnerability. It was hypothesized that the distress and crop failure against climate change, precisely crop-damaging temperatures forced them to commit suicide (Carleton, 2017).

2.2.1.2. Variables on exposure and functional relationship. Exposure of wheat growing agro-ecologies to climate change has been accounted by short-term and long-term changes respectively in weather and climate (Table 2). Month wise short-term variation and mean value for weather variables (TE 2015–16) like temperature, relative humidity, wind speed and rainfall during the *Rabi* months (November – April), the season during which wheat is cultivated was considered under exposure indicator. Month wise and overall long-term trend (1951–2010) for historical data on temperature (maximum, minimum and diurnal) and rainfall, relative humidity during the *Rabi* months were accounted for capturing the exposure of the agro-ecology to climate change and the coefficients were sourced from Rathore et al. (2013).

The long-term trend coefficients were estimated based on Mann–Kendall's non-parametric trend test and it has been established that climate variables affect wheat yield in the long-run (Sendhil et al., 2015). The unique approach in this study was considering only the variables pertaining to the crop growing season unlike other studies on vulnerability which has considered the full calendar year. The variables were selected based on data availability and owing to its yield sensitivity on different stages of crop growth (Sendhil et al., 2016; Sendhil et al., 2017a).

2.2.1.3. Variables on adaptive capacity and functional relationship. Variables that improve the potential of a wheat growing region to better suit the impact of climate change have been selected. A galore of literature supports that adaptive capacity of a region is influenced by education (Leichenko and O'Brien, 2002; Wood et al., 2014), irrigation (Cifdaloz et al., 2010; Huai, 2016; Thapa et al., 2016), farm revenue (Huai, 2016), share of rural poor in total or people under below poverty line (BPL) (Das, 2013), farm size and number (Gbetibouo and Ringler, 2009), share of agricultural GDP to total (Gbetibouo and Ringler, 2009), insurance (Milne, 2010; Panda et al., 2013). In the case of farm size it was conceptualised that smaller is the size of wheat farm, larger is the ability for adaptive capacity. The study has not emphasised the farmer capacity, but as such the land size capacity to cope with the climate change impact has been considered. Accordingly, rural literacy rate (2011 Census), area under irrigation (2013–14), net income (TE 2015–16), percentage of population below the poverty line (2011 census), average farm size (2011 census), Agriculture GDP share (TE 2015–16) and number of farmers insured under the weather based crop insurance scheme (six years average ending 2015–16) have been considered and their expected relationship with adaptive capacity is furnished in Table 3.

Table 2
Variables on exposure to climate change and their functional relationship.

Indicator	Variables	Functional relationship
Exposure	Month wise variation for weather variables (TE 2015–16) like temperature, relative humidity, wind speed and rainfall during the *Rabi* months (November–April) in %	Positive
	Mean value for weather variables (TE 2015–16) like temperature, relative humidity, wind speed and rainfall during the *Rabi* months (November–April) respectively in ^{0}C, %, km/hr and mm.	Positive
	Month wise trend coefficient (1951–2010) for variables like temperature (maximum, minimum and diurnal) and rainfall, relative humidity during the *Rabi* months (November–April)	Positive
	Long-term trend coefficient (1951–2010) for variables like temperature (maximum, minimum and diurnal) and rainfall, relative humidity during the *Rabi* months (November–April)	Positive

Note: TE refers to triennium ending.

Table 3
Variables on adaptive capacity to vulnerability and their functional relationship.

Indicator	Variables	Functional relationship
Adaptive capacity	Rural literacy rate (2011 Census) in %	Positive
	Area under irrigation (2013–14) in %	Positive
	Net income (TE 2015–16) in INR/ha	Positive
	% of rural population below poverty line (2011 Census)	Negative
	Average farm size (2011 Census) in hectares	Negative
	Agricultural GDP share (TE 2015–16) in %	Positive
	Number of farmers enrolled in weather based crop insurance (6 years average ending 2015–16)	Positive

Note: TE refers to triennium ending.

2.2.2. Normalisation of data

The collected data on different variables were normalised to make them unit and scale free for comparison using the approach as outlined in Kale et al. (2016); Kumar et al. (2016); Ponnusamy et al. (2016) and Mahida and Sendhil (2017) irrespective of study domain. For variables that have positive functional relationship with the respective indicators, normalisation has been done as given in Eq. (1).

$$Normalisation = \frac{Actual\ value - Minimum\ value}{Maximum\ value - Minimum\ value} \quad (1)$$

For variables that influence the respective indicators negatively, the following normalisation formula (Eq. (2)) has been used:

$$Normalisation = \frac{Maximum\ value - Actual\ value}{Maximum\ value - Minimum\ value} \quad (2)$$

2.2.3. Assigning weights to variables

After normalising the data which results in observations lying between 0 and 1 for all variables, weights have to be assigned to the respective variables for computing the composite index. Normally, weights can be assigned following three possible ways (Kumar et al., 2016): equal weights, expert opinion and principal component analysis (PCA). Each method has its own advantages and disadvantages. Equal weights may undermine some variables which largely influences the index; expert opinion will be subjective and limited to availability of experts, number of variables and research time to get the response; and PCA requires the econometric knowledge and works with the assumption that linear relationship exist among variables. In the present study, considering the use of multi-dimension data and advantage of PCA over other methods, weights have been assigned by performing the principal component analysis. Unlike studies which use only the factor loadings from first principal component for assigning weights (Kumar et al., 2016), we followed the Kaiser (1960) criterion (selecting the principal component with Eigen value more than one) which accounts for maximum variation in the data as given in Ayyoob et al. (2013), Rana et al. (2015), Kale et al. (2016), and Mahida and Sendhil (2017) under the following framework (Eq. (3)).

$$X_t = \Lambda_t F_t + e_t \quad (3)$$

where,

X_t represents the N-dimensional vector of variables influencing vulnerability,
Λ_t is the rx1 common factor,
F_t is the factor loading, and
e_t is the associated idiosyncratic error-term of order N × 1

The weights from the PCA were calculated as indicated by Eq. (4).

$$W_i = \sum |L_{ij}| E_j \quad (4)$$

where,

W_i is the weight of the i^{th} variable
E_j is the Eigen value of the j^{th} factor
L_{ij} is the loading value of the i^{th} variable on j^{th} factor.

2.2.4. Composite vulnerability indexing and categorisation

Expressing the above calculated weights for each variable for all the selected wheat producing states in the following formula (Eq. (5)) will give a composite index value for each state.

$$Index_{State} = \frac{\sum_{i=1}^{n} X_i W_i}{\sum_{i=1}^{j} W_i} \quad (5)$$

where,

X_i is the normalized value of i^{th} variable
W_i is the weight of the i^{th} variable

Finally, the composite vulnerability in wheat agro-ecologies have been classified into three categories viz., high, moderate and low based on the distribution of composite index value (Ayyoob et al., 2013; Rana et al., 2015; Kale et al., 2016).

High = Index $> (\overline{X} + 0.5\,\sigma)$
Moderate = $(\overline{X} - 0.5\sigma) \leqslant$ Index $\leqslant (\overline{X} + 0.5\,\sigma)$
Low = Index $< (\overline{X} - 0.5\,\sigma)$

3. Results and discussion

3.1. Sensitivity

Sensitivity indices for wheat growing states in India (Table 4) indicated that it was highest in Jharkhand (0.61) and lowest in Punjab (0.18) with a mean index of 0.45 and standard deviation of 0.12. A clear-cut regional disparity has been noticed in the sensitivity index owing to its wider range. Five states were classified as highly sensitive, seven as moderate and four as less sensitive to wheat production. The less sensitive states like Punjab, Haryana, Rajasthan and Uttar Pradesh were consistent performers of wheat with less instability in all the three variables *viz.*, area, production and yield (Ramdas et al., 2012). Their contribution to the national grain pool is also significant. In the case of

Table 4
Sensitivity index for wheat growing regions.

State	Sensitivity Index*	Category
Assam	0.47	Moderate
Bihar	0.45	Moderate
Chhattisgarh	0.54	High
Gujarat	0.45	Moderate
Haryana	0.32	Low
Himachal Pradesh	0.45	Moderate
Jharkhand	0.61	High
Karnataka	0.51	Moderate
Madhya Pradesh	0.58	High
Maharashtra	0.55	High
Odisha	0.57	High
Punjab	0.18	Low
Rajasthan	0.35	Low
Uttar Pradesh	0.32	Low
Uttarakhand	0.42	Moderate
West Bengal	0.50	Moderate

* Mean = 0.45 and Standard deviation = 0.12.

Jharkhand, the highest sensitive state, despite positive growth in production and area; the magnitude of instability was too high. Interestingly, the yield growth in the most sensitive state was found to be negative (Ramdas et al., 2012).

Among the variables considered for estimating the sensitivity, potential loss in production had the highest weightage (6.12) and lowest was for coefficient of variation in crop yield (3.74) which was obtained through the principal component analysis (PCA).[1] Potential loss in wheat production being a very important component of vulnerability, the state wise expected loss is furnished in Table 5. The average loss per annum was found to be more in Madhya Pradesh (6.17 million tonnes: 38.97%), followed by Uttar Pradesh (3.10 million tonnes: 19.62%) and Rajasthan (1.62 million tonnes: 10.21%). The loss in Madhya Pradesh is attributed to yield deviation effect (2.83 million tonnes), followed by area deviation effect (2.25 million tonnes) and area-yield interaction effect (1.09 million tonnes), respectively with a share of 45.95%, 36.41% and 17.64% (Fig. 2). Though Uttar Pradesh followed the pattern of Madhya Pradesh, Rajasthan exhibited a distinct pattern. In the case of Rajasthan which has been classified as low sensitive region, the area deviation effect contributed more to the potential loss (1.27 million tonnes: 78.48%), followed by yield deviation effect (17.19%) and area-yield interaction (4.33%). The country as a whole on an average incurred a potential loss of 15.82 million tonnes per annum which is largely accounted by yield deviation effect (8.75 million tonnes: 55.25%), followed by area deviation effect (5.67 million tonnes: 35.82%) and area-yield interaction (1.41 million tonnes: 8.91%). Perusal of Fig. 2 indicates that among states, the area deviation effect was highest in Odisha (78.78%) and lowest in Punjab (5.40%). On the contrary, for yield deviation effect, Punjab registered the highest (93.96%) and Odisha recorded the lowest (15.27%). The interaction effect was however highest in the case of Madhya Pradesh (17.64%) and lowest in Punjab (0.64%). Overall, the analysis highlighted the consequences of loss or risk to the nation if there is drastic change in the area and yield of the crop over a period of time. Hence, this variable assumes a lot of significance in estimating the sensitivity index of wheat agro-ecologies.

Table 5
State wise decomposition of potential loss in wheat production.

State	Potential loss ('000 tonnes)	State share in total potential loss (%)	Decomposition ('000 tonnes)		
			Area deviation	Yield deviation	Area-Yield interaction
Assam	18.91	0.12	13.65	4.74	0.52
Bihar	687.15	4.34	106.37	562.10	18.68
Chhattisgarh	33.81	0.21	10.34	21.03	2.44
Gujarat	637.42	4.03	359.87	238.06	39.49
Haryana	1270.02	8.03	364.35	863.31	42.36
Himachal Pradesh	137.65	0.87	9.70	126.58	1.38
Jharkhand	124.74	0.79	83.87	23.11	17.75
Karnataka	80.59	0.51	30.47	46.06	4.06
Madhya Pradesh	6166.51	38.97	2245.48	2833.47	1087.55
Maharashtra	356.90	2.26	187.85	145.89	23.17
Odisha	4.20	0.03	3.31	0.64	0.25
Punjab	1263.63	7.99	68.20	1187.34	8.08
Rajasthan	1615.92	10.21	1268.17	277.84	69.91
Uttar Pradesh	3104.79	19.62	766.09	2251.66	87.05
Uttarakhand	141.33	0.89	43.17	95.51	2.65
West Bengal	181.32	1.15	106.89	69.63	4.79
INDIA	15824.89	100	5667.77	8746.97	1410.15

3.2. Exposure

The analysis on exposure of wheat growing states to various month wise meteorological variables during the *Rabi* season (November to April) which is presented in Table 6, alarmed that Jharkhand registered the highest exposure (0.48), whereas Punjab was found to have the lowest exposure (0.30). However, the divergence in the exposure indices among states was very less (0.18) which explicitly indicates that almost all the regions were exposed to same short-term and long-term changes in the selected meteorological variables. The average exposure index for the selected states was 0.43 with a standard deviation of 0.05 which left eight states under high exposure, five under moderate and just three states categorised under low exposure.

Monthly mean temperature during the November month got the highest weight[2] (31.83) in estimating the exposure index. November is the crucial month for wheat sowing and it corroborates the findings of Sendhil et al. (2016). A 0.5 °C increase in the winter temperature shall reduce the crop duration by seven days coupled with yield reduction to the tune of 0.45 tonnes/ha (Sinha and Swaminathan, 1991). Following conventional wisdom that the temperature is increasing in the Central India, the indices revealed that the central Indian states covering full or partial regions of Chhattisgarh, Gujarat, Madhya Pradesh, Maharashtra, Odisha and Rajasthan fall under high to medium exposure. Despite mixed trend prevailing in the Northern India, states in the Indo-Gangetic plains witnessed a fall in the mean maximum temperatures during the months of January, February and March. Further, monthly mean minimum temperature has been increasing in Central India during October to December, March and April. In the case of monthly rainfall, spatially coherent increasing trends were observed in the month of February and decreasing trends in January and March for a majority of the states (Rathore et al., 2013).

3.3. Adaptive capacity

In the context of adaptive capacity of wheat growing regions, the mean index was 0.45 with a standard deviation of 0.13 (Table 7). State wise indices revealed that six were categorised as highly adaptive, five were found to be moderately adaptive and the rest five were labelled as states with low adaptive capacity with respect to vulnerability. Maharashtra has the highest adaptive capacity potential with an index value of 0.63, followed by Haryana (0.61) and Punjab (0.58). On the contrary, Jharkhand had the lowest adaptive capacity with an index value of 0.21. The higher net income of farmers, contribution of agricultural GDP and literacy rate in Maharashtra relative to other states influenced the state to be on the top of adaptive capacity score which had a weightage[3] of 3.06, 2.37 and 2.29 respectively, outweighed the state index in comparison to others. In case of Jharkhand, barring the average farm size, rest of the variables contributed less to the overall adaptive capacity of the state which made the region to be at the lower end. The huge divergence between the highest and lowest adaptive capacity indices alarmed that high inequality exists among wheat growing/producing states.

3.4. Composite vulnerability index

The composite vulnerability which is determined by sensitivity, adaptive capacity and exposure indicated a wide diversity in inter-index

[1] The data on normalisation of variables considered under sensitivity, weights for each variable derived from PCA and the result index for each state is given as supplementary information.

[2] The data on normalisation of variables considered under exposure, weights for each variable derived from PCA and the result index for each state is given as supplementary information.

[3] The data on normalisation of variables considered under adaptive capacity, weights for each variable derived from PCA and the result index for each state is given as supplementary information.

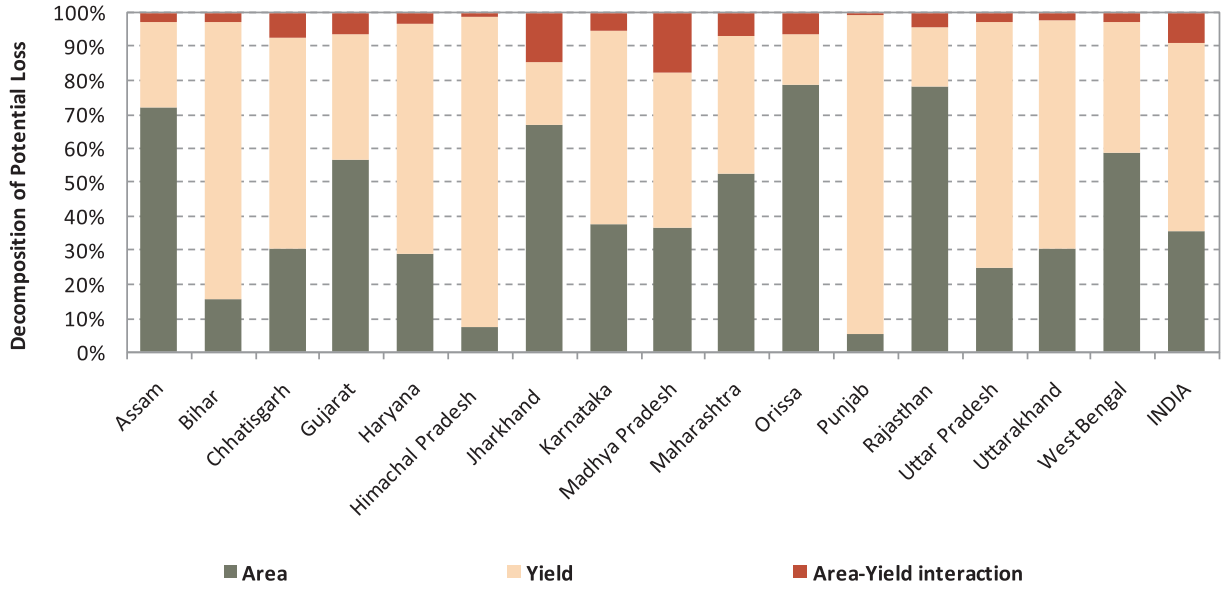


Fig. 2. Share of area, yield and area-yield interaction in potential loss of wheat production.

Table 6
Exposure index for wheat producing regions.

State	Exposure Index*	Category
Assam	0.45	Moderate
Bihar	0.47	High
Chhattisgarh	0.41	Moderate
Gujarat	0.47	High
Haryana	0.34	Low
Himachal Pradesh	0.44	Moderate
Jharkhand	0.48	High
Karnataka	0.48	High
Madhya Pradesh	0.43	Moderate
Maharashtra	0.47	High
Odisha	0.46	High
Punjab	0.30	Low
Rajasthan	0.41	Moderate
Uttar Pradesh	0.46	High
Uttarakhand	0.38	Low
West Bengal	0.46	High

* Mean = 0.43 and Standard deviation = 0.05.

Table 7
Adaptive capacity index for wheat producing regions.

State	Adaptive Capacity Index*	Category
Assam	0.24	Low
Bihar	0.42	Moderate
Chhattisgarh	0.25	Low
Gujarat	0.56	High
Haryana	0.61	High
Himachal Pradesh	0.48	Moderate
Jharkhand	0.21	Low
Karnataka	0.46	Moderate
Madhya Pradesh	0.37	Low
Maharashtra	0.63	High
Odisha	0.33	Low
Punjab	0.58	High
Rajasthan	0.54	High
Uttar Pradesh	0.54	High
Uttarakhand	0.51	Moderate
West Bengal	0.52	Moderate

* Mean = 0.45 and Standard deviation = 0.13.

magnitude. Barring Bihar and West Bengal, the inter-index values of three broad indicators of vulnerability exhibited a huge difference (Figs. 3 and 4). Fig. 3 gives the outlook on magnitude of indices whereas; Fig. 4 additionally presents the cross index diversity. The deviation among indices was more in the case of Punjab, followed by Haryana and Rajasthan. Adaptive capacity index was greater than the sensitivity and exposure for states like Gujarat, Haryana, Himachal Pradesh, Maharashtra, Punjab, Rajasthan, Uttar Pradesh, Uttarakhand and West Bengal. Shockingly, the sensitivity index was higher in Assam, Chhattisgarh, Jharkhand, Karnataka and Odisha in comparison to other broad indicators of vulnerability. Interestingly, Bihar was the only state with the exposure index higher than the rest of the two indices.

State wise vulnerability has been estimated *in lieu* of climate change and reported in Table 8. Punjab registered the lowest vulnerability (−0.09), followed by Haryana (0.05) and Rajasthan (0.21), whereas, Jharkhand has been labelled as the highest vulnerable region (0.88). Punjab's lowest index value is attributed to lowest sensitivity (0.18) as well as exposure (0.30). The potential impact in Punjab is relatively less than its adaptive capacity resulting in negative index. Additionally, the wheat growing state had the higher adaptive capacity (0.58). Similar pattern prevailed for Haryana and Rajasthan. Punjab and Haryana farmers in general are resourceful and hence their adaptive capacity is comparatively higher than others. However, a small amount of food-grain losses is expected in the agro-ecologies of Punjab, Haryana and western Uttar Pradesh (Sanghi et al., 1998) and around 10% production loss in wheat has been anticipated from the high yielding states of Punjab, Haryana and Uttar Pradesh (Sinha and Swaminathan, 1991).

Clearly, the analysis on vulnerability indicated that Jharkhand is most vulnerable and Punjab is the least vulnerable with respect to wheat cultivation (Table 8). Overall, five states were classified as highly vulnerable, six states under moderate and five under less vulnerable (Fig. 5). Mapping of vulnerability indices indicated that the central region is prone to high vulnerability in relation to other wheat agro-ecologies. A region with high exposure and sensitivity to the effects of climate change coupled with inadequate adaptive capacity to counter the ill-effects turns to be highly vulnerable. Likewise, an agro-ecology with excessive adaptation potential against the combined effect of exposure and sensitivity shall be labelled as least vulnerable (Smit et al., 1999; Smit and Wandel, 2006).

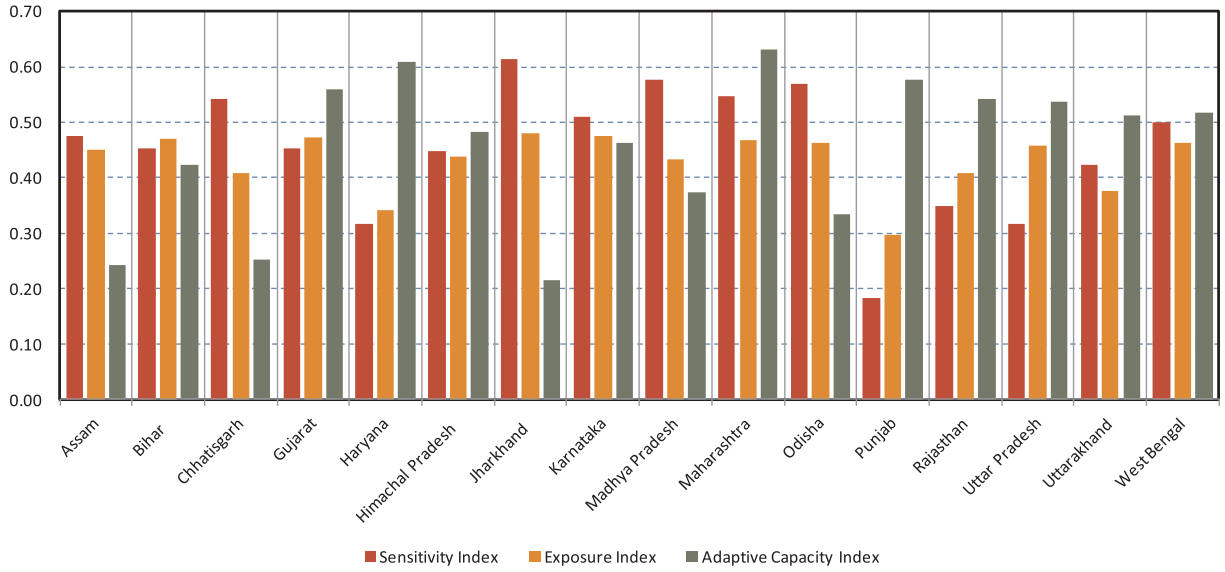


Fig. 3. A comparison of sensitivity, exposure and adaptive capacity indices.

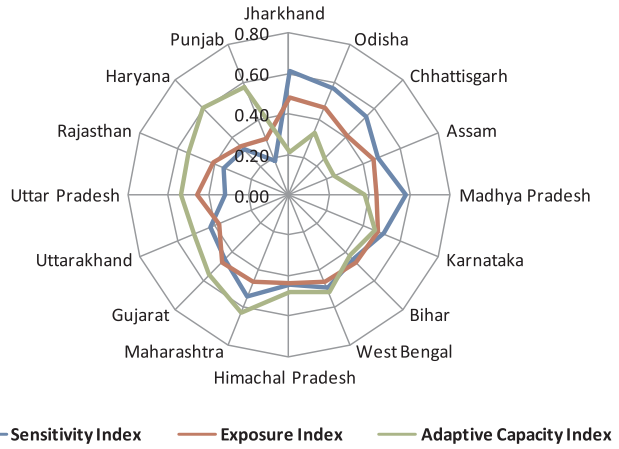


Fig. 4. Radar pictorial of sensitivity, exposure and adaptive capacity indices.

Table 8
Composite vulnerability indices in wheat production.

State	Vulnerability Index	Vulnerability Status
Assam	0.68	High
Bihar	0.50	Moderate
Chhattisgarh	0.70	High
Gujarat	0.37	Moderate
Haryana	0.05	Low
Himachal Pradesh	0.40	Moderate
Jharkhand	0.88	High
Karnataka	0.52	Moderate
Madhya Pradesh	0.64	High
Maharashtra	0.38	Moderate
Odisha	0.70	High
Punjab	−0.09	Low
Rajasthan	0.21	Low
Uttar Pradesh	0.24	Low
Uttarakhand	0.29	Low
West Bengal	0.45	Moderate

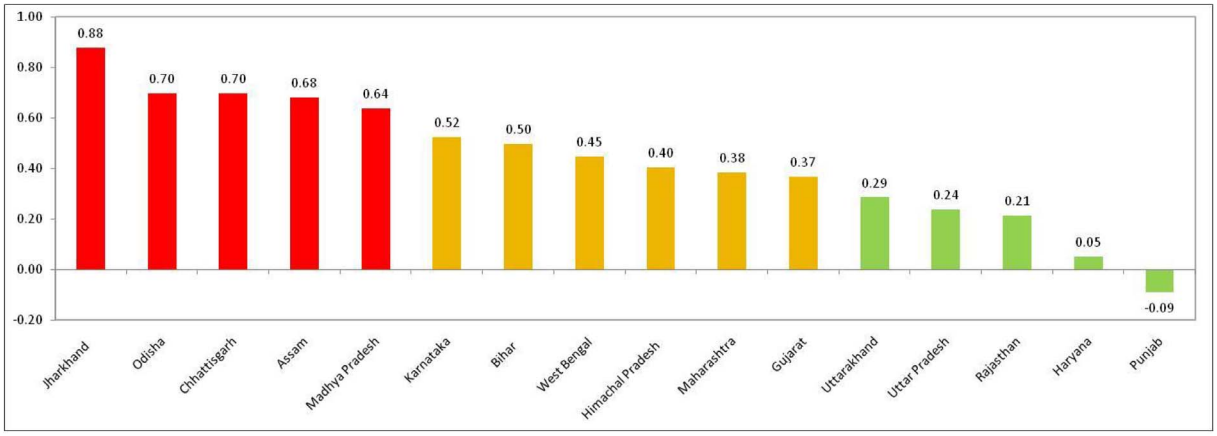
3.5. Quantification of area and production from different degree of vulnerability

Post estimating the degree of vulnerability in different wheat agro-ecologies, an attempt has been made to quantify the extent of area and production under each class of vulnerability (Table 9). Though a majority of the area coverage (18.88 million hectares: 62%) and production (67.90 million tonnes: 69%) comes from low vulnerable region, a significant amount of production (18.56 million tonnes: 19%) and area (6.38 million hectares: 21%) falls under high vulnerable region which is a matter of serious concern.

Policy initiatives should arise based on the regional share in area and production of wheat to the national total for coping with the negative impact of climate change. Hence, the state wise share in area and production was estimated for drawing conclusions (Figs. 6 and 7). Research, extension and policy support should focus on highly vulnerable regions by taking success stories or case studies from the low vulnerable regions embedded with high adaptive capacity. Clearly, Madhya Pradesh should be the prime focus at this stage owing to its significant contribution to the nation in wheat production. The state being classified under high vulnerable region, needs sufficient investment on research, infrastructure and social capital to manage climate change as well as to harness its potential in wheat production.

4. Conclusions

Indian agriculture is highly sensitive to climate change and any significant deviation from the business-as-usual scenario will affect the national food security. It is a biological and societal activity associated with a lot of day-to-day production risks and uncertainties across regions owing to its large dependency on monsoon. In the present study an attempt has been made to track the degree of vulnerability in wheat production/cultivation based on the region's sensitivity, exposure and adaptive capacity using cross-section and multi-dimension data for guiding policy makers to set priorities for management against climate change and variability. Vulnerability is the result of high instability in area, production and yield with significant potential loss which is a consequence of less adaptive capacity in that regions against the potential impact created by sensitivity and exposure variables. Vulnerability indexing and mapping alarmed that the states falling under central region of India is highly prone to production risk. To minimise the potential loss in wheat production, region-specific adaptation and climate smart farming practices have to be adopted in states like Madhya Pradesh, Uttar Pradesh and Rajasthan wherein the quantum of loss is significantly high due to area and yield deviation impact along with area-yield interaction effect. Highly vulnerable states holding a significant share in national wheat production like Madhya Pradesh should be the focus and priority for researchers, extension



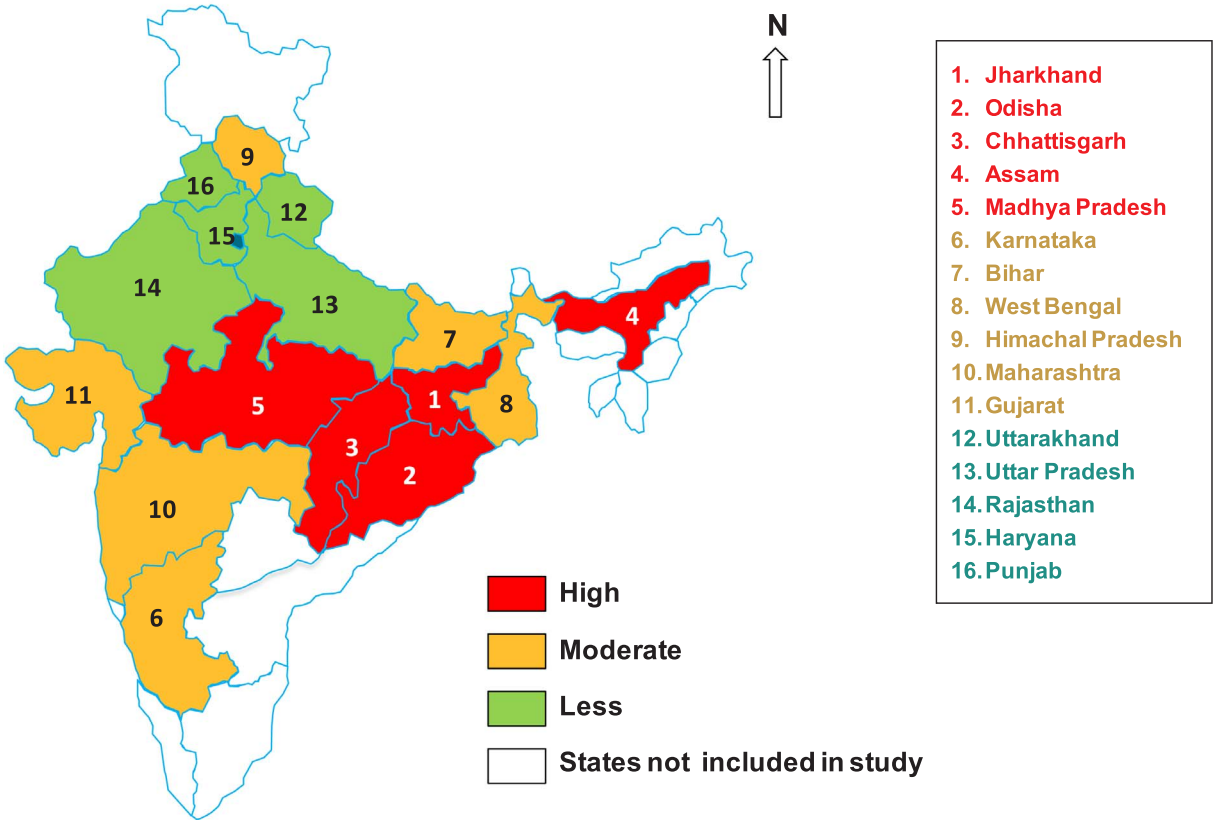


Fig. 5. Vulnerability classification and mapping for wheat.

Table 9
Quantification of vulnerability degree in crop acreage and production for 2016–17.

Degree of vulnerability	Area		Production	
	Million hectares	%	Million tonnes	%
High	6.38	21	18.56	19
Moderate	5.01	17	11.30	12
Low	18.88	62	67.90	69

agencies and policy makers to draw farm-specific and region-specific programs, plans and transfer of technologies. The state should take the success stories or farm models adopted in wheat agro-ecologies like Punjab and Haryana and follow it for reducing the losses as well as to manage the present status of vulnerability. Use of communication and information technologies for issuing advisories on crop management practices as well as weather forecast can be an effective tool to reach maximum number of farmers in less time. Already proven technologies like conservation agriculture practices, micro-irrigation and altering the

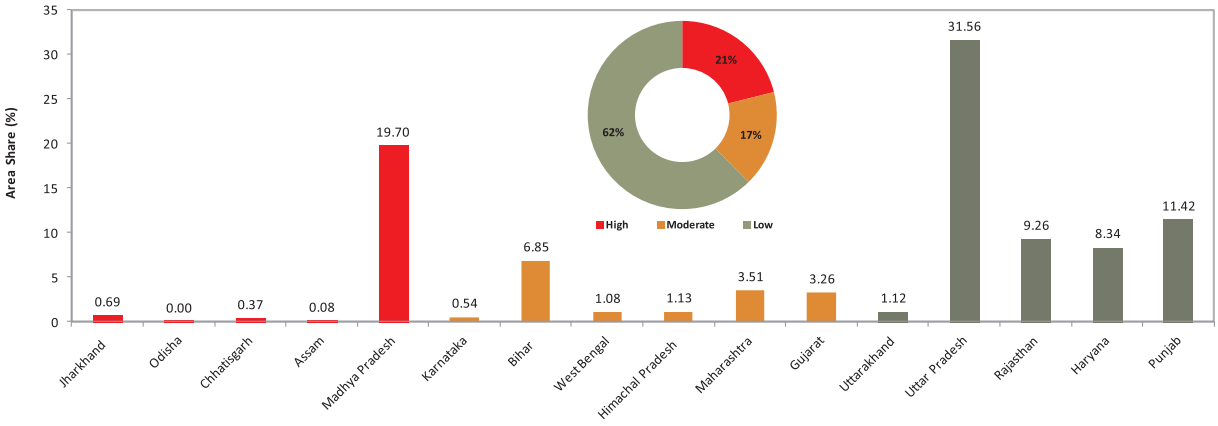


Fig. 6. Area share of pre-classified vulnerable regions in wheat.

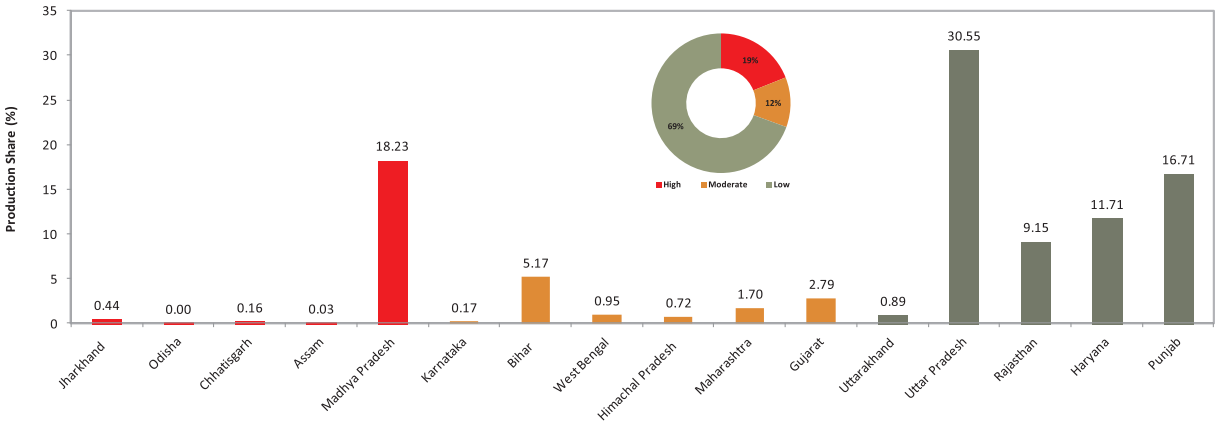


Fig. 7. Production share of pre-classified vulnerable regions in wheat.

sowing time according to weather forecast should be widely advocated and the suggested adaptive measures should warrant for sufficient investment plans and targets at all levels.

Acknowledgement

The authors duly thank for the support and infrastructure facilities rendered by the Director, ICAR-Indian Institute of Wheat and Barley Research, Karnal for carrying out the research [Project Code: CRSCIIWBRSIL201503400178].

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.ecolind.2018.02.053.

References

Acheampong, E.N., Ozor, N., Owusu, E.S., 2014. Vulnerability assessment of Northern Ghana to climate variability. Clim. Change 126 (1–2), 31–44.
Alexandrov, V., Eitzinger, J., Cajic, V., Oberforster, M., 2002. Potential impact of climate change on selected agricultural crops in north-eastern Austria. Glob. Change Biol. 8, 372–389 (10.1046/j.1354-1013.2002.00484.x).
Antwi-Agyei, P., Fraser, E.D., Dougill, A.J., Stringer, L.C., Simelton, E., 2012. Mapping the vulnerability of crop production to drought in Ghana using rainfall, yield and socioeconomic data. Appl. Geogr. 32 (2), 324–334.
Audsley, E., Pearn, K.R., Simota, C., Cojocaru, G., Koutsidou, E., Rounsevell, M.D.A., Trnka, M., Alexandrov, V., 2006. What can scenario modelling tell us about future European scale agricultural land-use, and what not? Environ. Sci. Policy 9, 148–162 (10.1016/j.envsci.2005.11.008).
Ayyoob, K.C., Krishnadas, M., Kaeel, C.M.H., 2013. Intra-regional disparities in agricultural development in Kerala. Agric. Update 8 (1&2), 103–106.
Cao, S., Lv, Y., Zheng, H., Wang, X., 2015. Research of the risk factors of China's unsustainable socioeconomic development: lessons for other nations. Soc. Indic. Res. 123 (2), 337–347.
Carleton, T.A., 2017. Crop-damaging temperatures increase suicide rates in India. Proc. Natl. Acad. Sci. U.S.A. 114 (33), 8746–8751. http://dx.doi.org/10.1073/pnas.1701354114.
Cifdaloz, O., Regmi, A., Anderies, J.M., Rodriguez, A.A., 2010. Robustness, vulnerability, and adaptive capacity in small-scale social-ecological systems: the Pumpa Irrigation system in Nepal. Available at. Ecol. Soc. 15 (3), 39. http://www.ecologyandsociety.org/vol15/iss3/art39/.
Climate Change, 2014. Synthesis Report, Headline statements are the overarching highlighted conclusions of the approved Summary for Policymakers which, taken together, provide a concise narrative. The four statements in boxes here are those summarizing the assessment in the Summary for Policymakers, sections 1–4.
Conway, G., 2009. The Science of Climate Change in Africa: Impacts and Adaptation, Grantham Institute for Climate Change Discussion Paper, pp. 24.
Das, 2013. Mapping the regional variation in potential vulnerability in Indian Agriculture to climate change – an exercise through constructing vulnerability index African. J. Environ. Sci. Technol. 7 (4), 112–121. http://dx.doi.org/10.5897/AJEST10.288.
DES, 2017. Directorate of Economics and Statistics, Ministry of Agriculture and Farmers Welfare, Government of India. http://eands.dacnet.nic.in/.
ECSJ, 2017. India: Highly Vulnerable to Climate Change, Bringing Science Forward http://www.ecsj2017.com/.
Ewert, F., Rounsevell, M.D.A., Reginster, I., Metzger, M.J., Leemans, R., 2005. Future scenarios of European agricultural land use I. Estimating changes in crop productivity. Agric. Ecosyst. Environ. 107, 101–116 (10.1016/j.agee.2004.12.003).
Gbetibouo, G.A., Ringler, C., 2009. Mapping South African Farming Sector Vulnerability to Climate Change and Variability: A Subnational Assessment. International Food Policy Research Institute Discussion Paper 00885, Washington DC.
Geng, Q., Wu, P., Zhao, X., Wang, Y., 2014. A framework of indicator system for zoning of agricultural water and land resources utilization: a case study of Bayan Nur, Inner Mongolia. Ecol. Indic. 40, 43–50.
Gornall, J., Betts, R., Burke, E., Clark, R., Camp, J., Willett, K., Wiltshire, A., 2010. Implications of climate change for agricultural productivity in the early twenty-first century. Philos. Trans. R Soc. Lond. B Biol. Sciv. 365 (1554), 2973–2989.
Hildén, M., Lehtonen, H., Bärlund, I., Hakala, K., Kaukoranta, T., Tattari, S., 2005. The practice and process of adaptation in Finnish agriculture. FINADAPT Working Paper 5, Finnish Environment Institute Mimeographs, no. 335 Helsinki, Finland: Finnish Environment Institute.
Huai, J., 2016. Role of livelihood capital in reducing climatic vulnerability: insights of

Australian wheat from 1990–2010. PLoS One 11 (3), e0152277. http://dx.doi.org/10.1371/journal.pone.0152277.
IPCC, 2007. Climate change 2007: Impacts, adaptation and vulnerability. In: Working Group II Contribution to the Intergovernmental Panel on Climate Change Fourth Assessment Report. Cambridge University Press, Cambridge.
Kaiser, H.F., 1960. The application of electronic computers to factor analysis. Educ. Psychol. Measure. 20, 141–151.
Kale, R.B., Ponnusamy, K., Chakravarty, A.K., Sendhil, R., Mohammad, A., 2016. Assessing resource and infrastructure disparities to strengthen Indian dairy sector. Ind. J. Anim. Sci. 86 (6), 720–725.
Kato, E., Ringler, C., Yesuf, M., Bryan, E., 2011. Soil and water conservation technologies: a buffer against production risk in the face of climate change? Insights from the Nile basin in Ethiopia. Agric. Econ. 42 (5), 593–604.
Kumar, S., Raizada, A., Biswas, H., Srinivas, S., Biswajit, M., 2016. Application of indicators for identifying climate change vulnerable areas in semi-arid regions of India. Ecolo. Indicators 70, 507–517.
Leichenko, R.M., O'Brien, K.L., 2002. The dynamics of rural vulnerability to global change: the case of southern Africa. Mitig. Adapt. Strat. Gl. 7 (1), 1–18.
Liu, X., Wang, Y., Peng, J., Braimoh, A.K., Yin, H., 2013. Assessing vulnerability to drought based on exposure, sensitivity and adaptive capacity: a case study in middle Inner Mongolia of China. Chin. Geogr. Sci. 23 (1), 13–25.
Mahida, D., Sendhil, R., 2017. Principal Component Analysis (PCA) based Indexing. A Chapter in the e-Compendium of Training-cum- Workshop on 'Data Analysis Tools and Approaches (DATA) in Agricultural Sciences' organised at the ICAR-IIWBR, India during March 22-24, 2017.
Maracchi, G., Sirotenko, O., Bindi, M., 2005. Impacts of present and future climate variability on agriculture and forestry in the temperate regions: Europe. Clim. Change 70, 117–135 (10.1007/s10584-005-5939-7).
Milne, J., 2010. Climate change, insurance and the building sector: synergisms, conflicts and adaptive capacity. Build. Res. Inform. 32 (1), 48–54.
Olesen, J.E., et al., 2007. Uncertainties in projected impacts of climate change on European agriculture and terrestrial ecosystems based on scenarios from regional climate models. Clim. Change 81, 123–143 (10.1007/s10584-006-9216-1).
Ortiz, R., Sayre, K.D., Govaerts, B., Gupta, R., Subbarao, G.V., Ban, T., Hodson, D., Dixon, J.M., Ivan Ortiz-Monsterio, J., Reynolds, M., 2008. Climate change: can wheat beat the heat? Agricult. Ecosyst. Environ. http://dx.doi.org/10.1016/j.agee.2008.01.019.
Panda, A., Sharma, U., Ninan, K.N., Patt, A., 2013. Adaptive capacity contributing to improved agricultural productivity at the household level: Empirical findings highlighting the importance of crop insurance. Glob. Environ. Change 23 (4), 782–790. http://dx.doi.org/10.1016/j.gloenvcha.2013.03.002.
Piya, L., Maharjan, K.L., Joshi, N.P., 2012. Vulnerability of rural households to climate change and extremes: analysis of Chepang households in the Mid-Hills of Nepal. In: 2012 Conference, August 18–24, 2012. Foz Do Iguacu, Brazil (No. 126191), International Association of Agricultural Economists.
Ponnusamy, K., Sendhil, R., Krishnan, M., 2016. Socio-economic development of fishers in Andhra Pradesh and Telangana states in India. Ind. J. Fish. 63 (3), 157–161.
Ramdas, S., Singh, R., Sharma, I., 2012. Exploring the performance of wheat production in India. J. Wheat Res. 4 (2), 37–44.
Rana, V., Ram, S., Sendhil, R., Nehra, K., Sharma, I., 2015. Physiological, biochemical and morphological study in wheat (*Triticum aestivum* L.) RILs population for salinity tolerance. J. Agril. Sci. 7, 119–128.
Rao, D.G., Sinha, S.K., 1994. Impact of climate change on simulated wheat production in India. In: Rosenzweig, C., Lglesias, A. (Eds.), Implications of Climate Change for International Agriculture: Crop Modeling Study. United States Environment Protection Agency, Washington, DC.
Rao, V.U.M., Rao, A.V.M.S., Kumar, P.V., Desai, S., Saikia, U.S., Srivsatava, N.N., Venkateswarlu, B., 2011. Agricultural Drought: climate change and Rainfed agriculture. In: Lecture Notes of the 5th SERC School, Central Research Institute for Dryland Agriculture, Hydrabad, India, p. 324.
Rathore, L.S., Attri, S.D., Jaiswal A.K., 2013. State Level Climate Change Trends in India, Indian Meteorological Department, Ministry of Earth Science, Government of India, pp. 1–147.
Richter, G.M., Semenov, M.A., 2005. Modelling impacts of climate change on wheat yields in England and Wales: assessing drought risks. Agric. Syst. 84, 77–97. http://dx.doi.org/10.1016/j.agsy.2004.06.011.
Sanghi, A., Mendelsohn, R., Dinar, A., 1998. The climate sensitivity of Indian agriculture. In Measuring the Impact of Climate Change on Indian Agriculture, edited by Dinar, A., Mendelsohn, R., Everson, Parika, J., Sanghi, A., Kumar, K., Mckinsey, J., Lonergan, S. The World Bank [Technical Paper No 402], Washington, DC.
Sendhil, R., Jha, A., Kumar, A., Singh S., 2017a. Tracking Wheat Yield Sensitivity to Weather Variability across Indian Transect for Climate Smart Farming, Extramural Project Report, ICAR-Indian Institute of Wheat and Barley Research, Karnal. pp. 1–40.
Sendhil, R., Jha, A., Kumar, A., Singh, S., Kharub, A.S., 2017b. Status of vulnerability in wheat and barley producing states of India. J. Wheat Res. 9 (1), 60–63.
Sendhil, R., Meena, R.P., Thimmappa, K., Singh, R., Sharma, I., 2015. Sensitivity of rice-wheat system yields to climate change: evidence from Haryana. Kar. J. Agril. Sci. 28 (5), 797–802.
Sendhil, R., Ramasundaram, P., Meena, R.P., Thimmappa, K., Sharma, I., 2016. Tracking the yield sensitivity of rice-wheat system to weather anomalies. Natl. Acad. Sci. Lett. 39 (6), 401–405 (10.1007/s40009-016-0485-6).
Sharma, I., Sendhil, R., Chatrath, R., 2015. Regional disparity and distribution gains in wheat production. A Chapter in the Souvenir of 54th AIW&B workers meet Workers' meet, Sardarkrushinagar Dantiwada Agricultural University, Gujarat from 21-24 August, 2015.
Sinha, S.K., Swaminathan, M.S., 1991. Deforestation, climate change and sustainable nutrition security: a case study of India. Clim. Change 19, 201–209.
Smit, B., Burton, I., Klein, R.J.T., Street, R., 1999. The science of adaptation: a framework for assessment. Mitig. Adapt. Strat. Glob. Change 4, 199–213.
Smit, B., Wandel, J., 2006. Adaptation, adaptive capacity and vulnerability. Glob. Environ. Change 16 (3), 282–292.
Thapa, B., Scott, C., Wester, P., Varady, R., 2016. Towards characterizing the adaptive capacity of farmer-managed irrigation systems: learnings from Nepal. Curr. Opin. Environ. Sustain. 21, 37–44.
Tuck, G., Glendining, M.J., Smith, P., House, J.I., Wattenbach, M., 2006. The potential distribution of bioenergy crops in Europe under present and future climate. Biomass Bioenergy 30, 183–197. http://dx.doi.org/10.1016/j.biombioe.2005.11.019.
Wood, S.A., Jina, A.S., Jain, M., Kristjanson, P., DeFries, R.S., 2014. Smallholder farmer cropping decisions related to climate variability across multiple regions. Glob. Environ. Change 25, 163–172.
World Bank, 2003. Report on Financing Rapid Onset Natural Disaster Losses in India: A Risk Management Approach. Report No. 26844-IN. World Bank, Washington, DC.